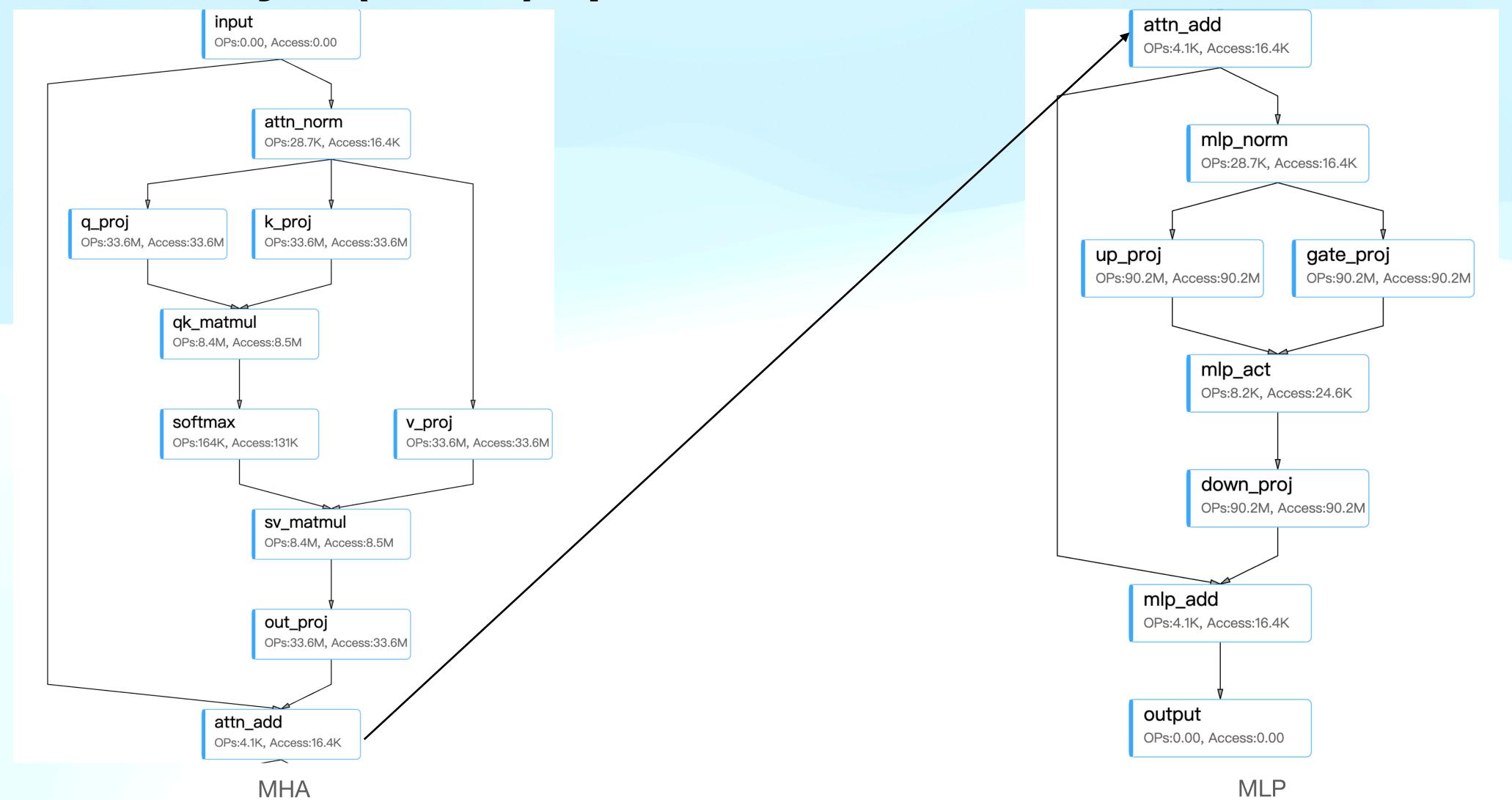
# Kernel Optimization

Profile result

- Profile
  - End-to-End operation analysis
  - Kernel implemented by Flashinfer
- Fuse all kernel to one

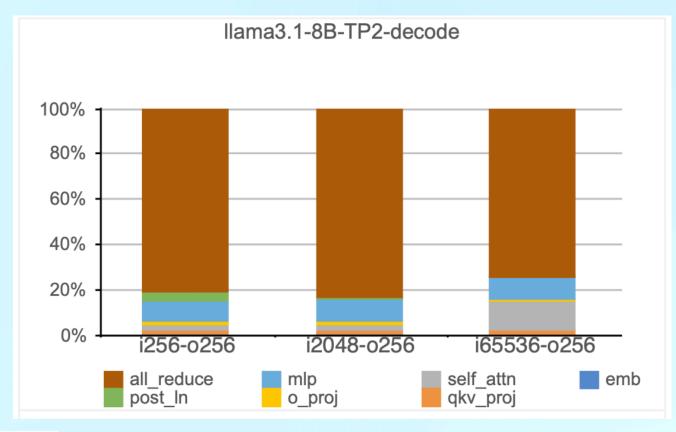
#### End-to-End Analysis

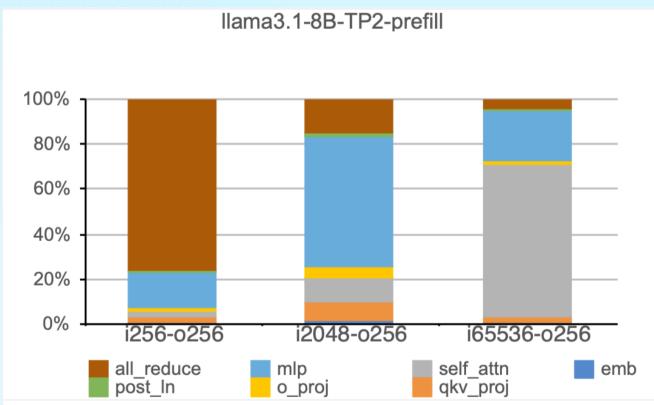
Transformer layer (Llama) operation

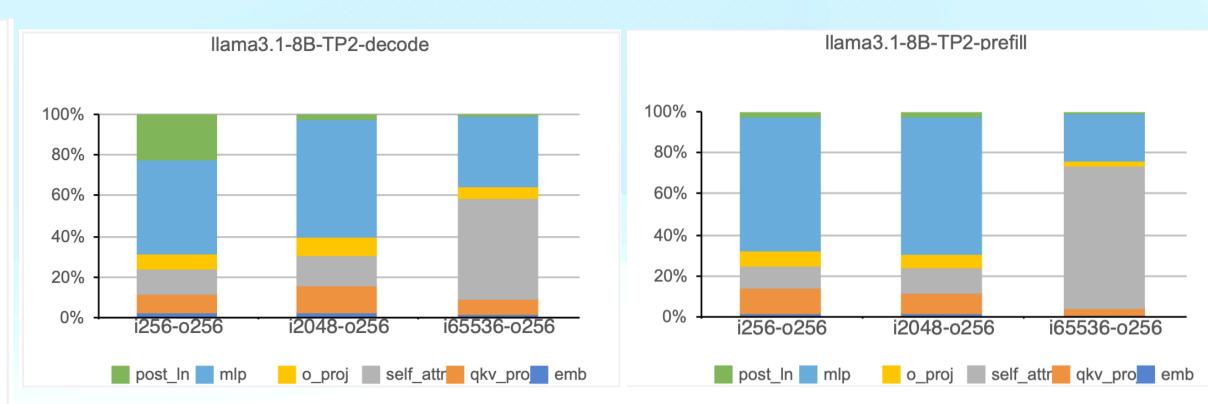


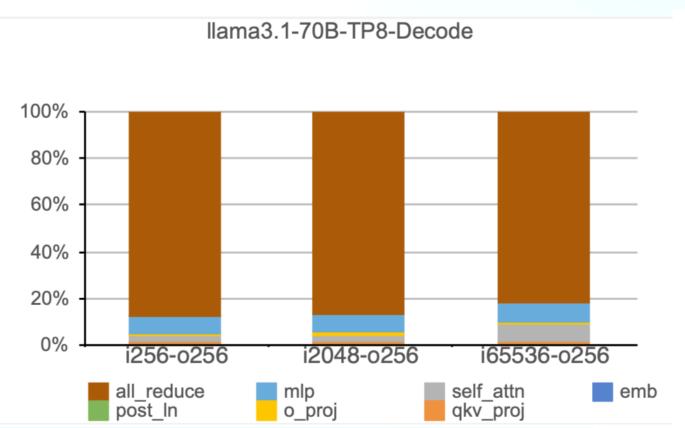
# End-to-End Analysis

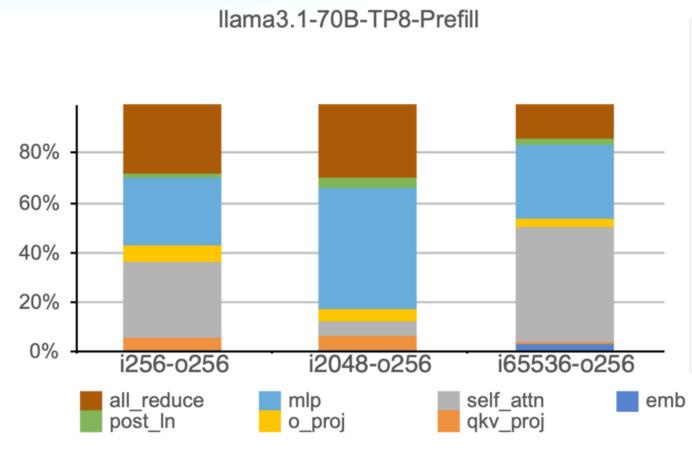
#### Llama3.1 operation ratio

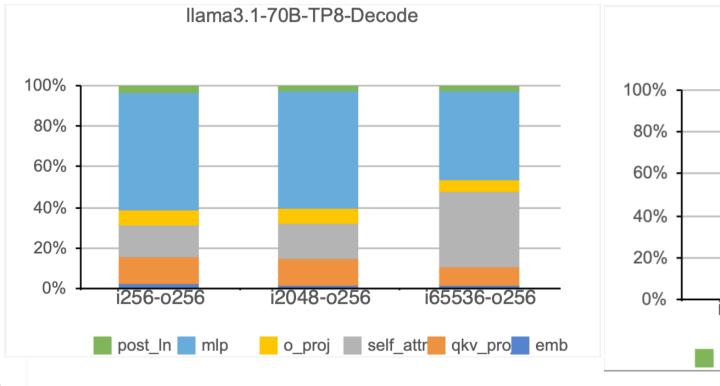


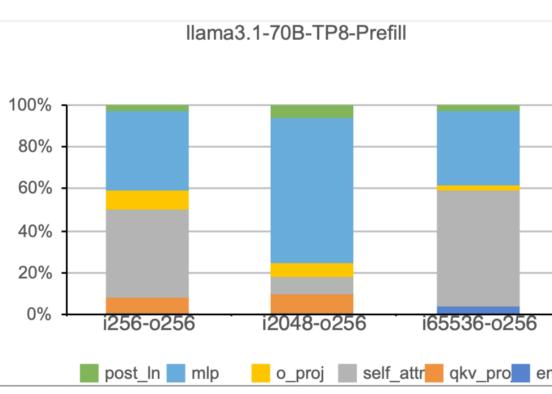






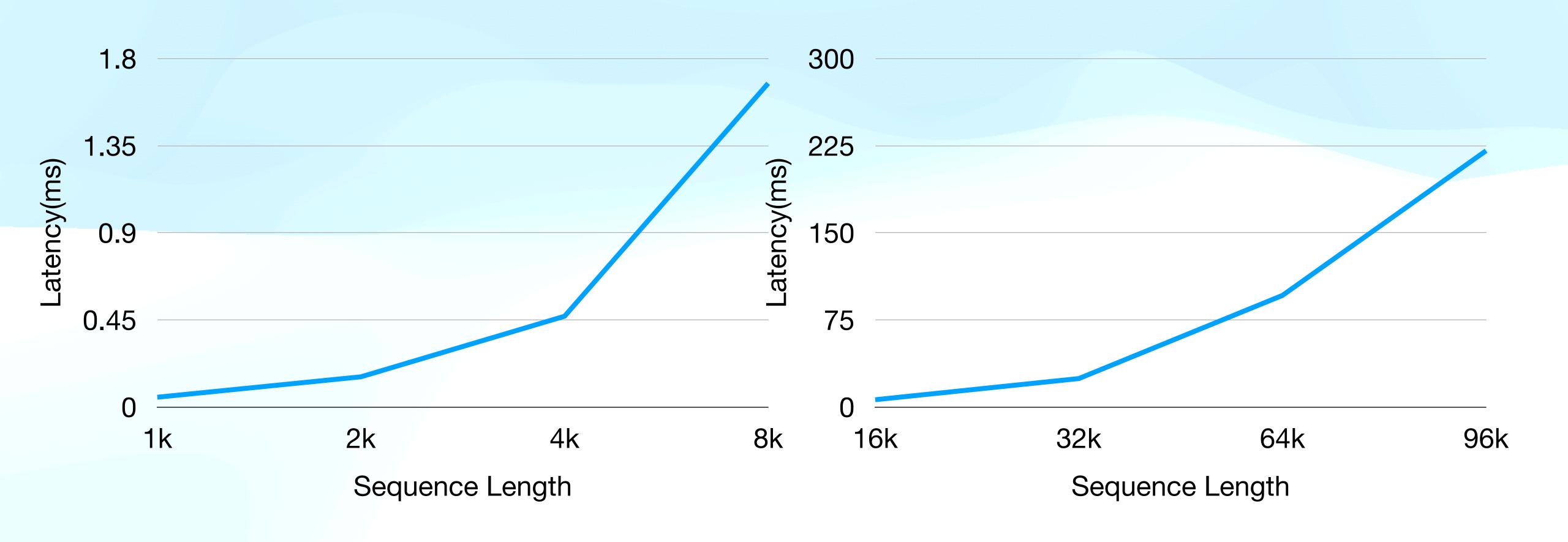






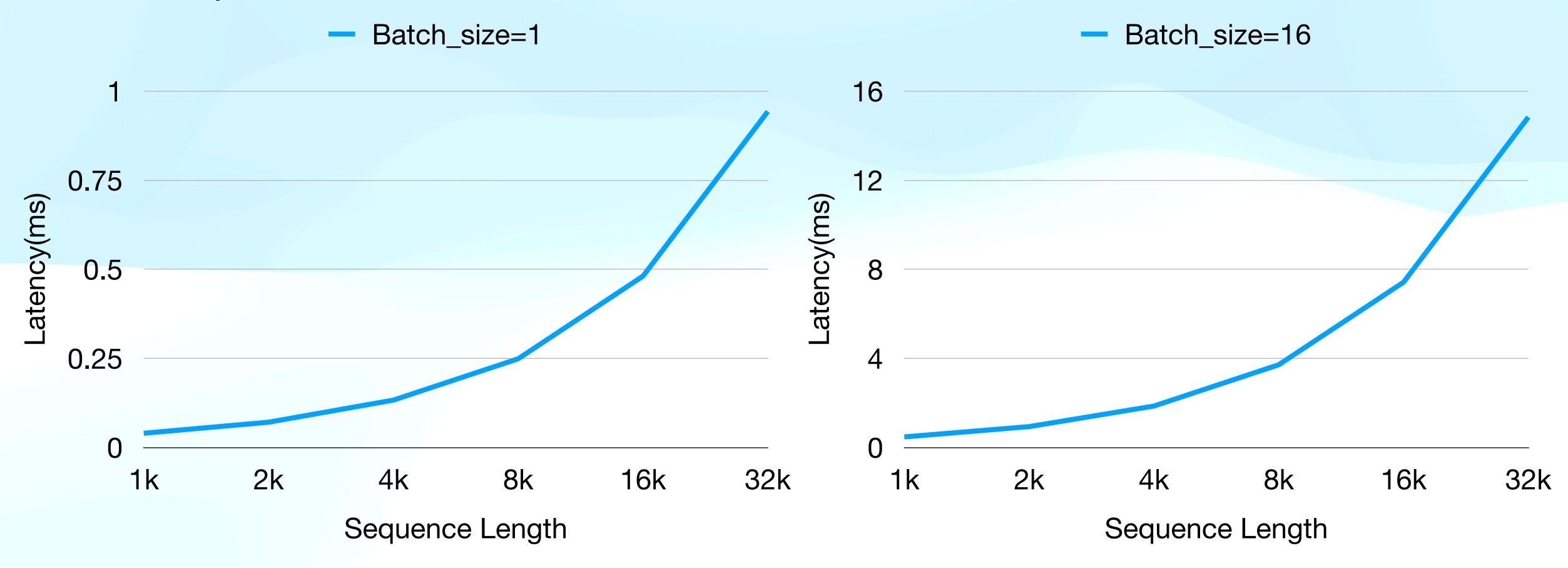
## Attention Kernel Latency

Prefill phase

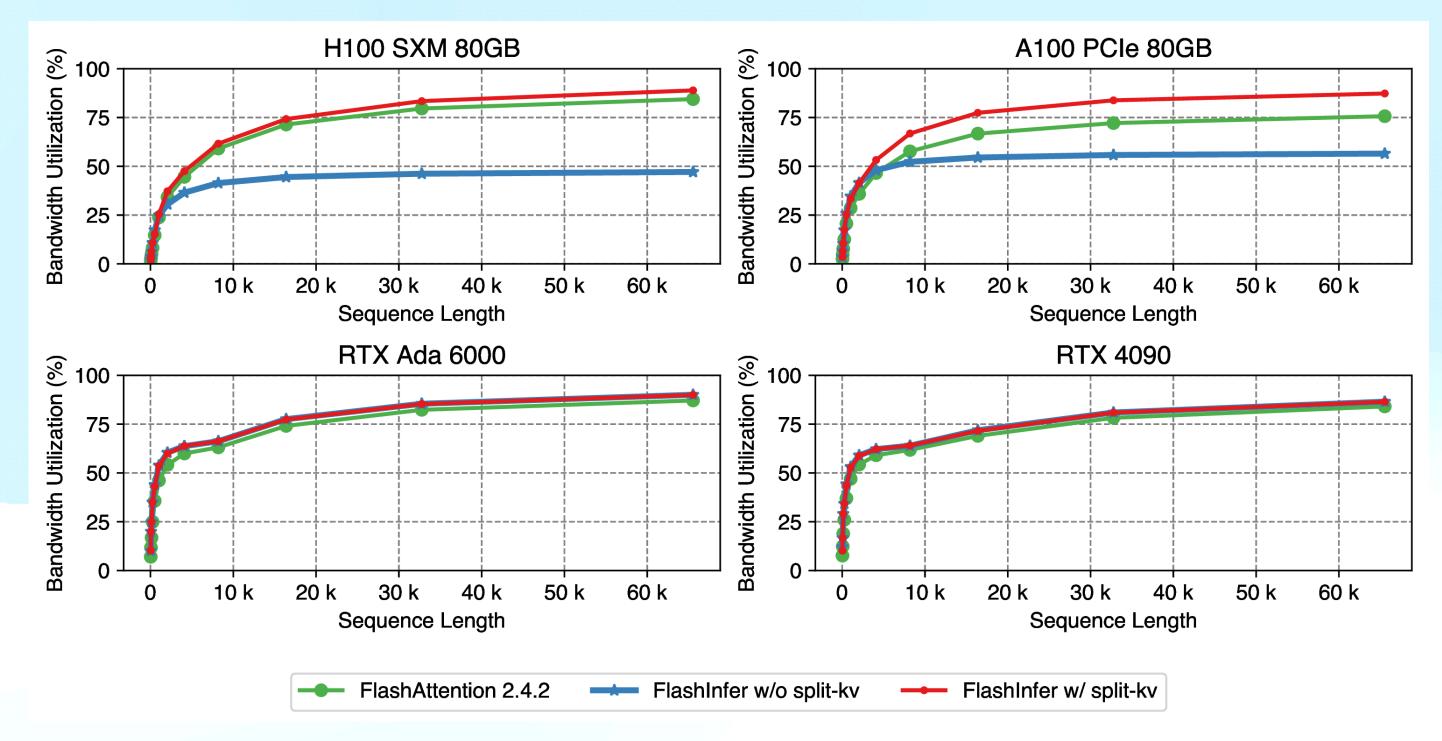


## Attention Kernel Latency

Decode phase



## Profile Analysis



Single request decode kernel GPU utilization

	CuBLAS	H100 Peak Tensor Cores Performance
TFlops	670	989

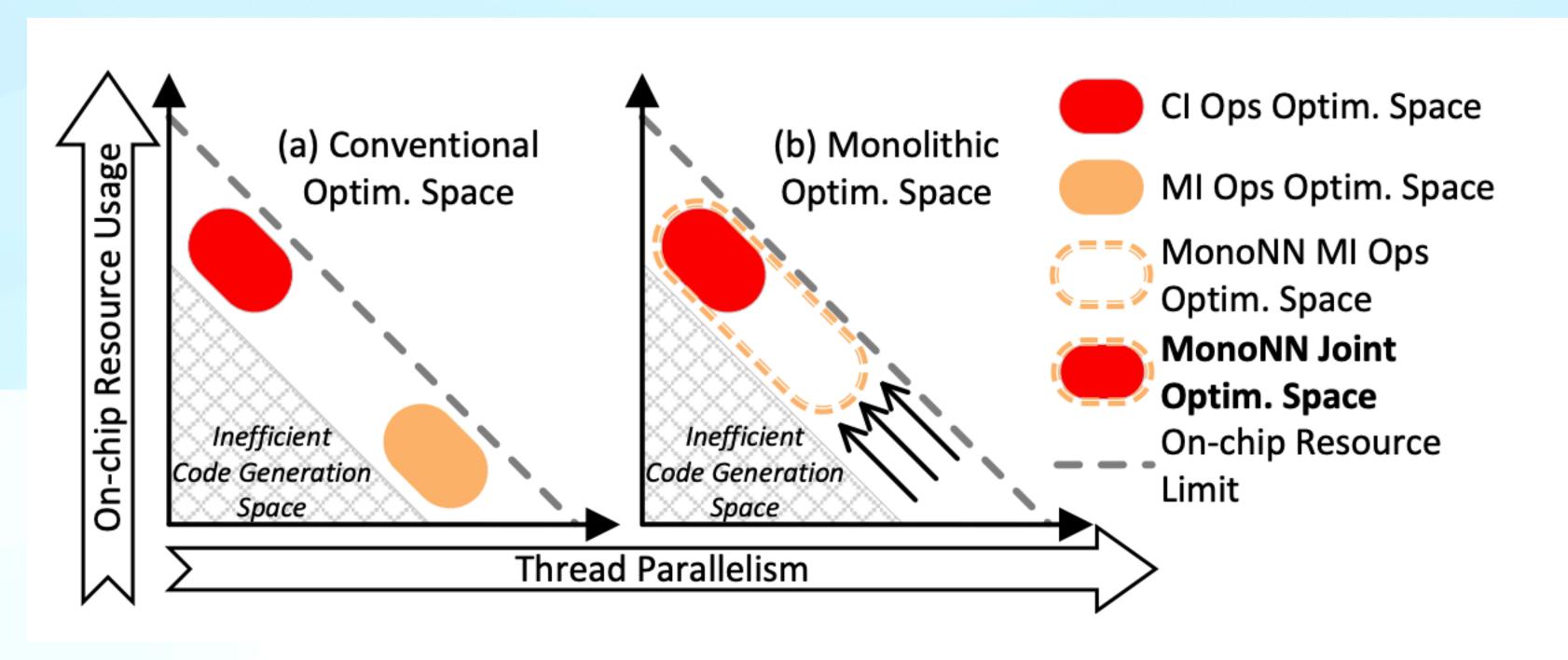
**CuBLAS GEMM Performance** 

We can try to optimize through fusing all kernel to one for better end-to-end performance.

# Fuse all kernel to one Challenges

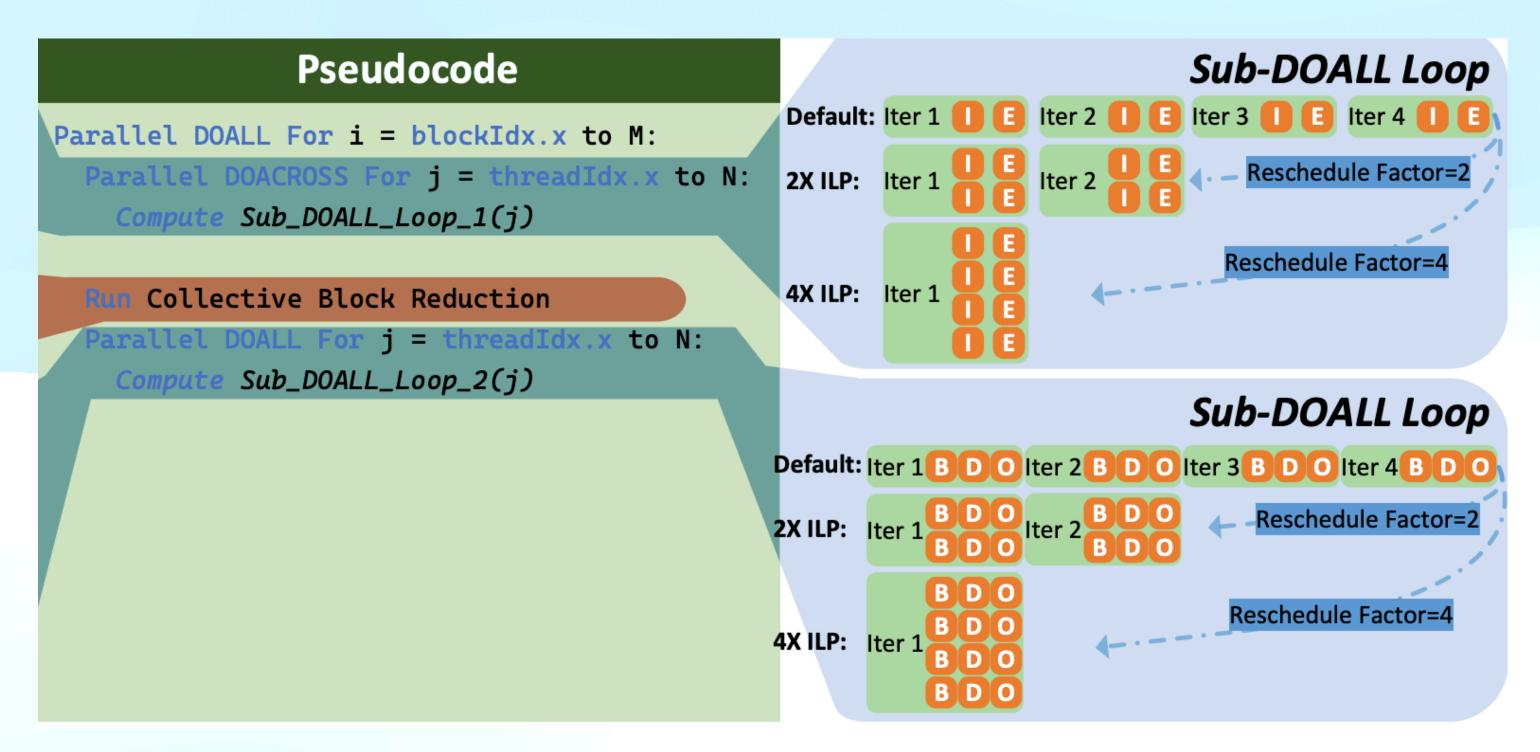
- Resource incompatibility between computeintensive and memory-intensive operators.
  - Compute-intensive operators require a large amount of on-chip resources (registers and shared memory)
  - Memory-intensive ops rely on massive concurrent threads to hide off-chip memory access(TLP).

#### A High-level illustrate



Align the optimization space of MI Ops as closely as possible with that of CI Ops

#### **Detailed Implementation**

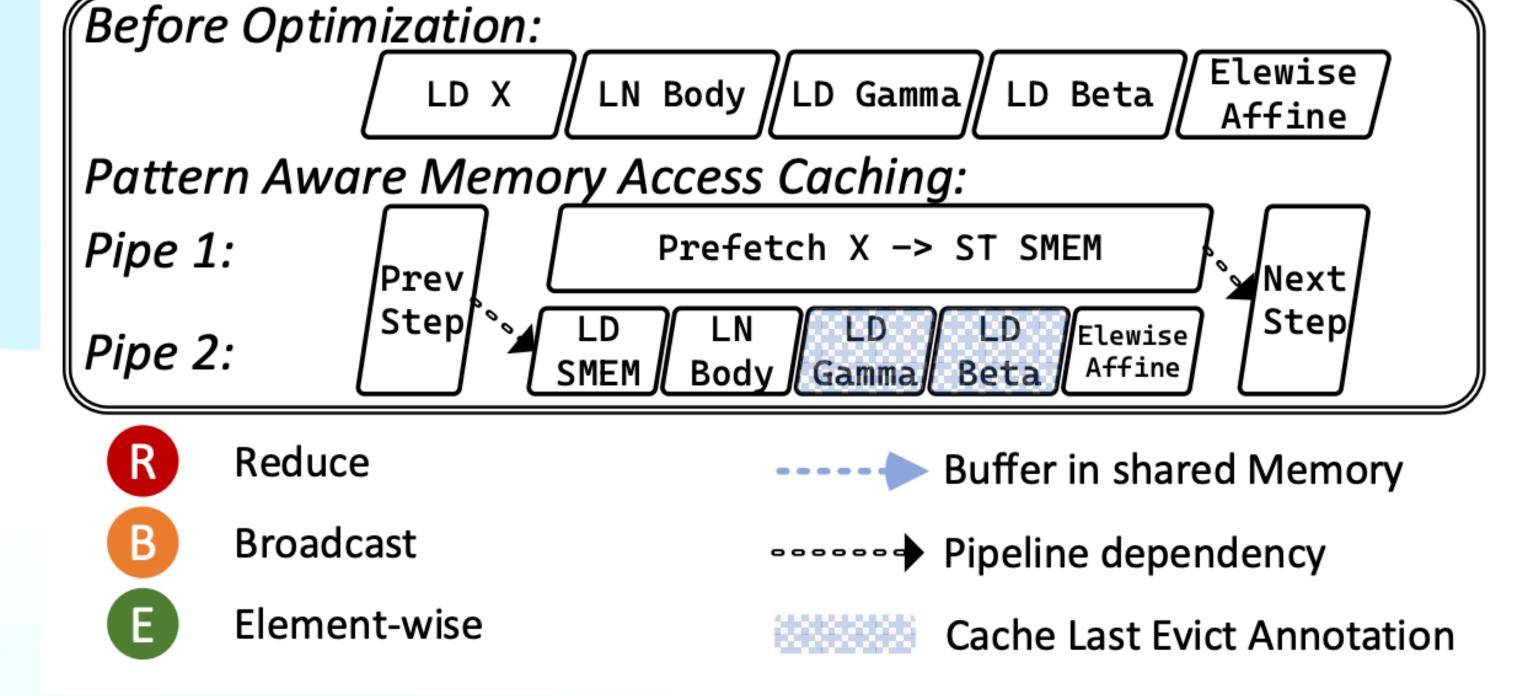


Context-aware instruction rescheduling for softmax computation.

Context-aware instruction rescheduling:
For memory-intensive operator(softmax),
we can use ILP(Loop unroll) which need
more on-chip resources adaptive with

compute-intensive operator(GEMM).

#### **Detailed Implementation**



Memory access optimizations:

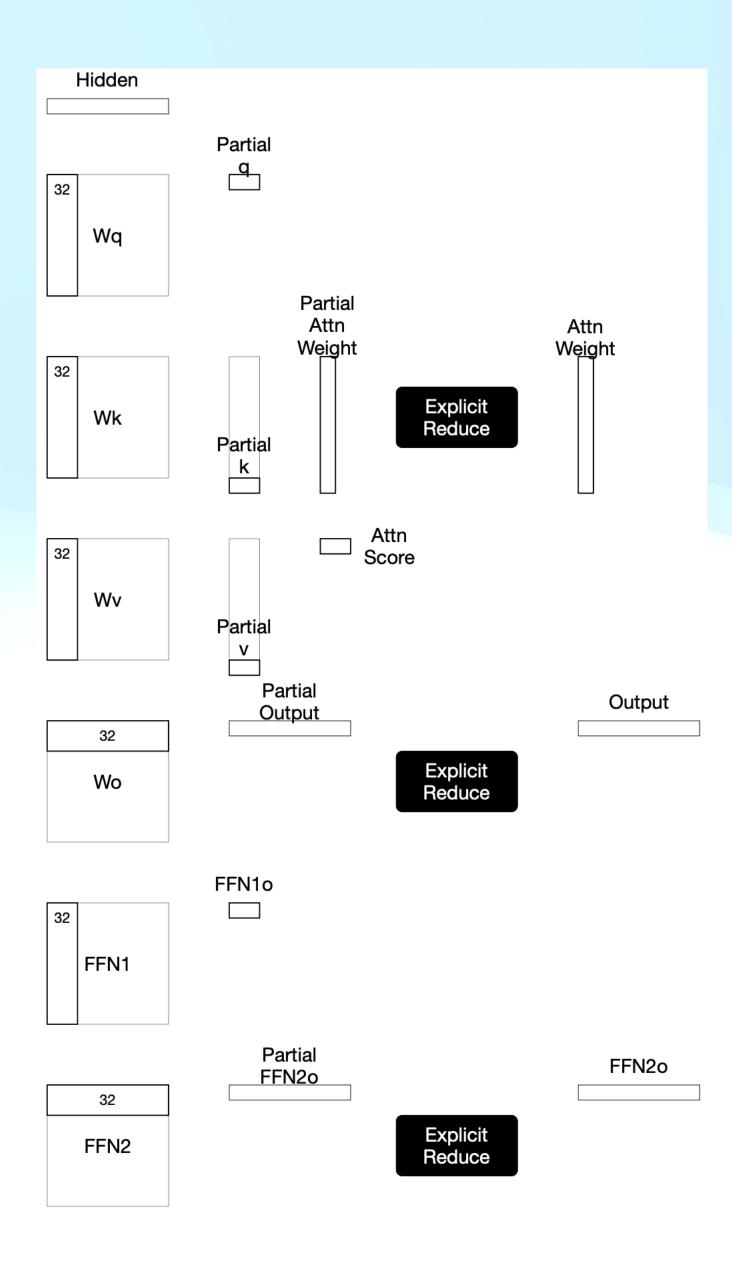
Leverages the abundant shared memory resource

allocated by the compute-intensive computation

in one kernel to pipeline the global memory access

On-chip resource exploitation

Fuse decode phase to one



# Thanks